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Networked Logistics and Additive Manufacturing

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Abstract

Additive manufacturing has the potential to fundamentally change how military expeditionary operations are conducted. By manufacturing spare parts in remote sites, rather than relying on lengthy and extensive supply chains or remaining tethered to an "iron mountain" of logistics support, the expeditionary units have the potential to be more agile, to maintain their readiness at high levels while deployed, and to extend their operational reach. We describe how the additive manufacturing capability can be combined with a networked logistics approach for the U.S. Marine Corps. The ultimate goal is to develop a logistics support structure that is more resilient to enemy attacks and provides improved support to the forward units.

Introduction

Additive manufacturing (AM) has enjoyed success in a number of specialty fields. Potential benefits for expeditionary units include achieving higher readiness at lower cost, because deployed units can use AM to create replacement parts at or near the point of demand, rather than either relying on carrying large quantities of spare parts or dealing with long lead-times for replacements. Another potential benefit is the ability to reduce wastage of the materials used in the three-dimensional (3D) printing process and subsequent post-treatments by only producing what is needed. Finally, if the same compounds can be used to manufacture a variety of parts, AM could help forward-deployed units maintain a high level of readiness while dramatically reducing their logistics footprint.

To realize this potential, program managers have several decisions to make. They must determine how best to acquire AM capabilities, what classes of components are suitable for AM, whether the resulting structural stability and reliability are comparable for components made using AM and current methods, and how differences in reliability may affect the supply chain and readiness levels. If the suitability and reliability are not factored into the decision-making process, then AM may end up being a costly and largely redundant logistics system running in parallel with the current supply chain, rather than being a transformative capability.

AM is integrally tied with Department of Defense (DoD) acquisition programs in several ways. First, the capability for AM must be procured. Rather than setting specifications and requirements for parts or component parts, the program managers must set requirements for AM processes that are capable of 3D-printing and subsequent finishing operations in order to produce items that meet the necessary specifications for the parts or component parts. Second, although the flexibility of AM is often touted, the issues of the quality and reliability of the resulting parts are not generally considered—or, these characteristics are considered in isolation, rather than via their effects on the supply chain and operational effectiveness. An implicit assumption in much of the literature is that the resultant parts will be as capable when produced using AM as they are when produced using standard manufacturing techniques. Third, the current roadmap for employing AM in DoD operations is incremental in nature. For example, the U.S. Army's phases for AM are (1) determining how AM can be used to repair or replace existing parts, (2) using AM to produce a single part rather than assembling multiple component parts, and (3) using AM to create parts that do not currently exist (U.S. Army, 2017). The Marine Corps and Navy have similar guidance (Department of the Navy, 2017; Department of the Navy, Headquarters United States Marine Corps, 2017).

In this paper, we present a model-based framework for a transformative rather than an incremental approach for incorporating AM technologies within the DoD. We do so by creating a simulation model of networked expeditionary logistics operations—a concept of operations that now may be possible. Because stockpiles of spare parts are no longer the only way of ensuring that the combat logistics element is fully supporting the expeditionary units, we can explore the simulation model's behavior to gain insight about other alternatives.

Background

We begin with a short overview of several key areas that motivate this research. Our discussion is meant to be illustrative, not exhaustive.

Additive Manufacturing: Previous Research Themes

There has been a rapid escalation of additive manufacturing research and applications in recent years. It has already demonstrated success in specific industries, where computer-controlled 3D printing using a variety of compounds has opened up new customization possibilities for manufactured parts. For example, the medical field has enjoyed success in customizing polymeric parts, such as right-sizing cardiovascular stents rather than relying on a limited number of sizes. Custom-sized biodegradable stents reduce the risks of complications that arise if an ill-fitting stent moves and ultimately fails, and additional surgery is required to repair or replace the stent (Hodsden, 2016); they can be quite beneficial for infants and children who need temporary assistance while they are growing (Fessenden, 2013). Other successful applications have been reported in areas ranging from sports equipment (Graziosi et al., 2017) to spare parts for air-cooling ducts of the environmental control system for F-18 fighter jets (Khajavi et al., 2013) to 3D-printed jet engines (Sturmer, 2015).

Previous research related to AM falls into a few general categories. The first is research related to the AM process itself, including the polymeric, metal alloy, or composite materials used in the 3D printing part of the process, along with the post-treatment operations required for the materials to attain their structural capabilities (Frazier, 2014). Post-treatment operations, once the printing process is complete, can include various types of heat treatment to reduce porosity or induce the desired microstructures and properties such as annealing or hot isostatic pressing.

A second stream of research involves studying the logistics supply chain, contrasting AM versus traditional manufacturing for producing spare parts. This has been accomplished in different ways. Case study approaches have been used as part of an inductive research approach, such as the work by Oettmeier (2016), who conducts and describes semi-structured interviews for three focal firms, suppliers, and customers for AM devices in the medical industry. Oettmeier concludes that the effects of AM technology adoption on the supply chain configuration are context-specific and depend on a number of exogenous and supply chain-related factors. Mellor et al. (2014) also use a qualitative case study approach to create a normative structural model of AM implementation, including factors related to the technology and supply chain, as well as other structural and strategic aspects of the organization. See, for example, Silva and Renzende (2013) for further discussion of logistics implications of additive manufacturing for a number of different industries.

Other research examines the life-cycle cost of AM relative to traditional manufacturing techniques. For example, Westerweel et al. (2018) develop an analytic cost model and conduct a full factorial experiment involving seven factors, each at three levels, to gain some managerial insights. They conclude that logistics savings can occur because of the reduced production lead time inherent in AM. They also find that large investments in AM are attractive if there are large numbers of systems with long life cycles, and if the reliability of the AM parts is quite close to that of the parts produced by the original equipment manufacturer (OEM). Still others have looked at the supply chain for the powders used in AM applications, rather than focusing on the supply chain associated with OEM parts (Dawes et al., 2015).

Additive Manufacturing for Expeditionary Operations

With regard to military operations, U.S. Army Chief of Staff General M. A. Milley stated, "The convergence of new developments such as ubiquitous information technology and personal communications, proliferation of precision guided weapons, robotics and on-site 3D printing, and rapidly growing urbanization all augur a very different era of warfare" (Barno & Bensahel, 2017). AM may be beneficial for legacy systems as well, if the original parts are no longer being manufactured but custom AM parts can be made as needed.

An example of a simulation-based assessment of AM for military operations appears in Moore et al. (2018). They create forecasts of replacement parts for the M109A6 Paladin self-propelled 155mm Howitzer, based on data obtained from the U.S. Army during the initial stage of Operation Iraqi Freedom (OIF). They use these data-driven forecasts as inputs to a simulation model to assess the feasibility of integrating AM into the Army's supply chain for 48 different combinations of the three factors: the echelon at which the AM is placed, the printing speed, and the available volume of metallic compounds for printing the metal parts. They recommend that "the Army needs to continue experimenting with AM facilities in the field under realistic demand rates and operating environments," and also suggest that AM should most likely start with small items where quality control requirements are not so onerous. Other nations are also intrigued by the prospect of incorporating AM into military logistics support (Ng, 2018).

Some AM approaches are more suitable for harsh and variable environments than others, in part due to their safety requirements. Zelinski (2019) describes how metallic 3D printing that involves arc-welding metallic compounds deposited by solid wire feed, or by high-velocity cold spray of metal powder, can be relatively safe. In contrast, the safety requirements for setting up and using laser melting systems may prohibit those forms of AM in some operational environments.

Logistics for Expeditionary Operations: Current System

The resources contained in these stockpiles are critical to the survival of a military force and directly contribute to their mission success. An adversary capable of destroying these stockpiles or significantly deteriorating the supply distribution process can seriously disrupt or even halt military operations.

A graphical representation of an iron mountain logistics approach appears in Figure 1 based on a scenario from Lynch (2019), who considers expeditionary operations at the Marine Expeditionary Unit (MEU) level. In this graphic (not to scale), we show how the current system often works. The seabase is treated as an essentially unlimited floating warehouse of supplies and fuel. The ultimate goal is meeting the logistics needs of the supported units—in this scenario, two infantry units and a Forward Arming and Refueling Point (FARP). Each infantry unit represents a standard Marine Corps Infantry Rifle Company. FARPs do not have a standard size, but the FARP in this scenario is roughly equivalent to the size of an infantry platoon. Most supplies are moved by ship-to-shore connectors from the seabase to a fixed, fortified, onshore position—the so-called “iron mountain,” although jet fuel is typically delivered to the FARP by air assets. The supported units each generate requests for several different types of supply items. Some supplies—such as Meals Ready to Eat (MREs), bottled water, and general fuel consumption—are used at rates proportional to the number of personnel in the unit. Ammunition and missile usage are less predictable and depend on the operational tempo. The convoys tend to make regular deliveries over long distances and are comprised of many logistics vehicles (LVs) as well as security vehicles for added protection. The black boxes notionally represent the amounts of supplies at various points in the system. For example, the seabase is typically assumed to have (or have access to) unlimited inventory; the iron mountain has a very large supply on hand; the convoys carry large amounts in each delivery; and the supported units must keep enough on hand for sustainment between convoy arrivals. Of course, this does not capture the full complexity of logistics support in real-world military operations.

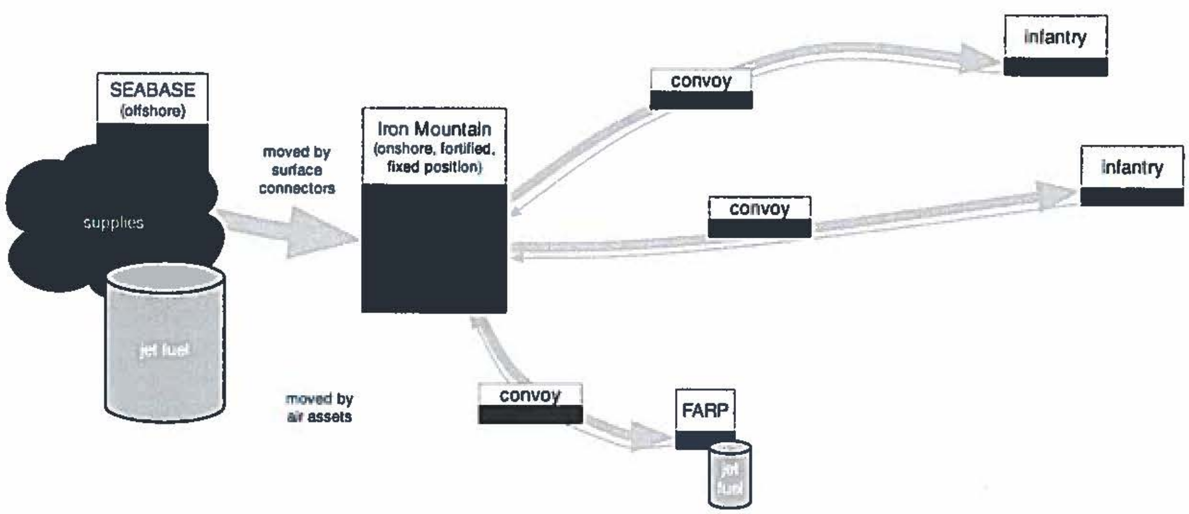


Figure 1. Current Logistics Supply Movement in Expeditionary Operations

As mentioned earlier, plans for using AM in expeditionary operations in the near future focus on its potential for repairing or replacing existing parts. By injecting this capability into an existing logistics chain, the primary benefits are those of reducing the storage capacity and lead time for replacement parts without adversely affecting readiness. Parts that can be easily manufactured using AM technologies can range from those used steadily throughout the operations, to rarely-needed replacement parts for mission-critical items. In either situation, it may require less storage volume to ship bulk raw materials (e.g., metallic powders) and manufacture the parts as needed, than to store and access completed parts. Easy access can be particularly problematic in very high-density storage systems such as the hold of a ship (Gue, 2006), or in limited staging areas where containers transferred from ships may await other transportation to their final destinations (Gue & Kang, 2001).

For the logistics system of Figure 1, there are three places in which adding AM capability might be beneficial: the seabase, the iron mountain, and the supported units themselves. Each has benefits and drawbacks. The seabase is often considered the most secure, and on larger ships, it may be possible to set up dedicated AM facilities (including appropriate post-treatment stations) with access to a ready supply of bulk raw materials. Lead-times for 3D printing replacement parts at the seabase may be less than lead-times for receiving them from the United States or other regional supplier. The iron mountain has similar capabilities, although there may be less control of some environmental characteristics (heat, humidity, dust, vibration) that might affect the AM production schedule or the resulting quality and reliability of the parts. Lead times for 3D-printed parts from the iron mountain might be less than those of 3D-printed parts from the seabase, particularly if small numbers of items are needed. Adding AM capability directly to the supported units has both potential benefits and potential drawbacks. On one hand, it may reduce the lead time for replacement parts even further. On the other hand, it may be the most likely to be adversely impacted by weather conditions, and long post-treatment requirements may either reduce the unit's mobility or result in less reliable replacement parts.

Networked Logistics for Expeditionary Operations

Headquarters U.S. Marine Corps recently published the Marine Corps Operating Concept (MOC), which states the Marine Corps must "[redesign] our logistics to support distributable forces across a dynamic and fully contested battlespace—because iron mountains of supply and lakes of liquid fuel are liabilities and not supportive of maneuver warfare" (Department of the Navy, 2016, p. 9).

During the wars in Iraq and Afghanistan, the insurgent forces were incapable of conducting an attack on the scale required to destroy a large base containing massive quantities of supplies. Attacks such as those on Camp Bastion and Camp Shorabak caused damage and some casualties (to Afghan troops) but did not pose a serious threat for the viability of the entire bases and their operations (Shah et al., 2019; Snow, 2019). As the United States has transitioned to preparing for a conflict with a near-peer adversary, this is no longer true: an iron mountain is a very enticing target.

Even in situations where enemy actions are not a concern, iron mountains can still be liabilities. The 2010 fire in the Supply Management Unit lot in Camp Leatherneck, Afghanistan, is one such example: Although the fire was eventually contained with no casualties, most of the inventory was destroyed—including construction materials, medical supplies, and repair parts (Pelczar, 2010). In this way, a networked logistics structure may add resilience.

Consequently, a new method of providing logistics support to expeditionary forces is needed. Lynch (2019) creates a simulation model intended to help analysts explore the function of a networked logistics force. A simplified graphical representation appears in Figure 2. Instead of consolidating and distributing supplies from a large, stationary iron mountain, the supplies are redistributed to smaller logistics support nodes that occasionally move around the battlefield. There are three types of units that require support from these logistics nodes: infantry units and a Forward Arming and Refueling Point (FARP) as in Figure 1, as well as a shore-based missile. The shore-based missile unit is based on a platoon from the Army High Mobility Artillery Rock System (HIMARS) Battalion, because providing shore-based missile support is "a relatively new concept for the Marine Corps" (Lynch, 2019).

The supported units each generate requests for several different types of supply items. Some supplies—such as Meals Ready to Eat (MREs), bottled water, and general fuel consumption—are used at rates proportional to the number of personnel in the unit. Ammunition and missile requests are randomly generated, providing an implicit rather than explicit representation of their use during combat operations. The supplies are loaded on logistics vehicles (LVs) for delivery. For the current model instantiation, each LV can be considered a truck that carries supplies on pallets.

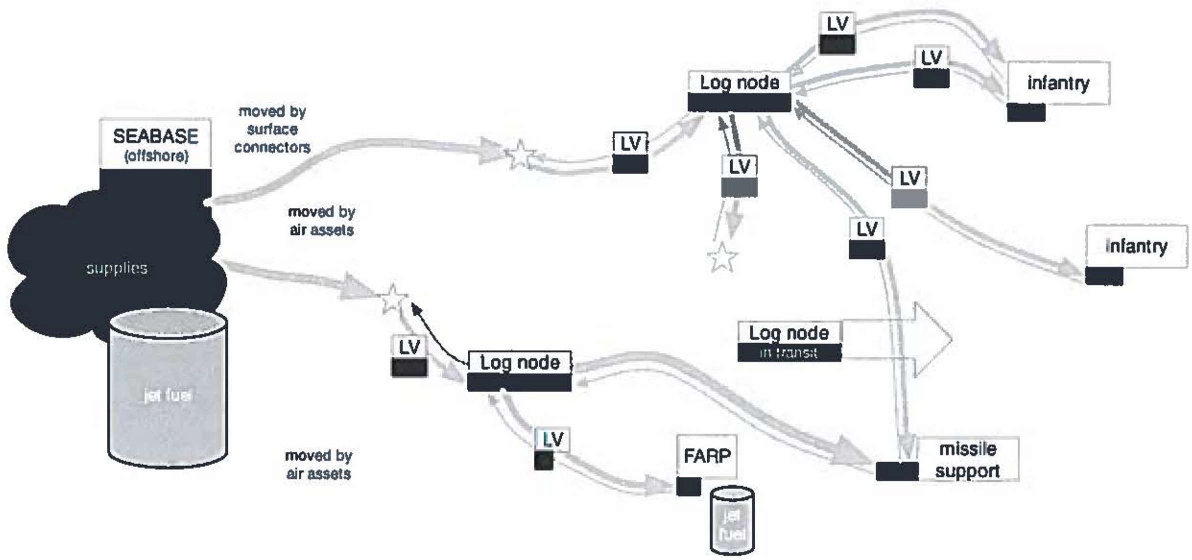


Figure 2. Logistics Supply Movement in Expeditionary Operations

The networked logistics of Figure 2 is clearly more complex than that of Figure 1, as can be seen by the larger number of potential routes taken by LVs. The networked logistics structure is highly dynamic, as the supported units, logistics nodes, and rendezvous points can all change over time. Ideally, this dynamic structure will enhance the maneuverability of the forward units and make the force less vulnerable to attacks by a near-peer adversary. There are other differences as well. The black boxes that represent the amounts of supplies at various locations in the network tend to be much smaller than those in Figure 1. This has the potential to increase the agility and extend the operational reach of the supported units. However, care must be taken to ensure they are mission-capable despite their decreased logistical footprint.

Table 1 provides a brief comparison of the iron mountain and networked expeditionary logistics structures.

Table 1. Differences Between Current and Networked Expeditionary Logistics Systems

Element	Assumptions: Iron Mountain Logistics	Assumptions: Iron Network Logistics
Seabase	Offshore, invulnerable, infinite capacity	Offshore, invulnerable, infinite capacity
Supported units	Two infantry, one FARP	Two infantry, one FARP, one shore-based missile support
Onshore logistics element	Iron mountain: immobile, heavily fortified, very large capacity, regularly resupplied from seabase	Logistics nodes: mobile, self-sufficient, use their own logistics vehicles (LVs) to change logistics node locations in a single trip, resupply from fixed or ad hoc rendezvous points
Seabase -> onshore	Large deliveries to fixed location at fairly regular intervals	Smaller deliveries to LVs at both fixed and ad hoc rendezvous points
Convoys	Large, heavily armed, long and regular trips to supported units	Single LVs travel faster, make frequent short trips to supported units, less predictable transit routes

There are several places where AM capabilities might be added to the iron network: at the seabase, at the logistics nodes, or at the supported units. The same basic benefits and drawbacks apply. Stationary units (i.e., the seabase) can be heavily protected, and AM may reduce storage and lead time requirements. Still, the mobility of the logistics nodes and the use of single LVs rather than large convoys may affect the way AM is implemented, or vice versa. If AM is added at logistics nodes, then those nodes must wait to change locations until all post-printing treatments are complete. Both the duration of AM operations and timing of logistics node moves are decisions that must be made.

Lynch (2019) implements the networked logistics simulation model using the Ruby programming language. Each run of the simulation represents 180 days of operation, beginning from a time where all supplies have arrived at the seabase and each logistics node and supported unit has the supplies it needs to begin operations. Logistics nodes and supported units all use supplies over time; the logistics nodes are handled as internal requests that require no transportation as long as the node has the requested supplies on hand. Each logistics node will move its location after filling a specified number of requests. The LVs begin moving to a requesting unit as soon as either the LV is nearly full (e.g., seven or more of eight pallet spaces filled), or the request has been waiting a sufficiently long time. Logistics nodes place requests for resupply to the seabase whenever their inventories drop below specified levels but can also receive direct shipments by air if needed.

A few other modeling choices deserve mention. LVs can encounter breakdowns or enemy attacks at random times during transit. If an LV suffers a maintenance breakdown, that delays the delivery process by a relatively short amount of time (hours to days). If an enemy attack occurs, there is some probability that the LV wards it off successfully and then continues on after a short delay; there is also some probability that the attack is successful and the LV and its inventory are all destroyed. In the latter situation, new requests are automatically generated for all destroyed items.

Another key assumption is that inventory levels are visible to all players in the simulation. This is essential because in the situation in which one logistics element cannot provide support requested by a unit, it must then pass that request to another logistics node. Trust in the logistics structure is also critical in practice (Spangenberg, 2017). Without that trust, each unit has incentives to hoard items or make larger requests than necessary, which may keep the logistics footprint large or reduce the agility of the force.

For further details of this networked logistics simulation model, see Lynch (2019).

Research Methodology: Data Farming

Headquarters U.S. Marine Corps recently published the Marine Corps Operating Concept (MOC), which states the Marine Corps must "[redesign] our logistics to support distributable forces across a dynamic and fully contested battlespace—because iron mountains of supply and lakes of liquid fu

Data farming and data mining are different! Lucas et al. (2015) compare and contrast these metaphors as follows:

> Miners seek valuable nuggets of ore buried in the earth, but have no control over what is out there or how hard it is to extract the nuggets from their surroundings. As they take samples from the earth they gather more information about the underlying geology. Similarly, data miners seek to uncover valuable nuggets of information buried within massive amounts of data. Data-mining techniques use statistical and graphical measures to try to identify interesting correlations or clusters in the data set.
>
> Farmers cultivate the land to maximize their yield. They manipulate the environment to their advantage using irrigation, pest control, crop rotation, fertilizer, and more. Small-scale designed experiments let them determine whether these treatments are effective. Similarly, data farmers manipulate simulation models to their advantage, using large-scale designed experimentation to grow data from their models in a manner that easily lets them extract useful information. ... [The output data sets] also contain better data, in the sense that the results can reveal root cause-and-effect relationships between the model input factors and the model responses, in addition to rich graphical and statistical views of these relationships. (p. 297)

The building blocks of data farming are a collaborative approach to rapid scenario prototyping, modeling platform development, design of experiments, high performance computing, and the analysis and visualization of the output—all with the intent of providing decision-makers with timely insights (NATO, 2014). Of these, design of experiments is key: it is the only way to break the so-called "curse of dimensionality." For example, suppose our simulation has 100 inputs (i.e., factors), each factor has two levels (low and high) of interest, and we decide to look at all combinations. A single replication of this experiment would require over 178 millennia on the world's fastest supercomputer (the Summit at Oakridge National Laboratories), even if each of the 2100 (roughly 1030) simulation runs consisted of a single machine instruction! Yet efficient experiment designs enable us to run interesting simulation models with dozens or hundreds of factors on a modern laptop or small computing cluster in a matter of days to hours, taking the study from the realm of the impossible to the realm of the practical.

A data farming approach is useful for the networked logistics study because the simulation model has a large number of potential factors, and the ways in which they affect the system performance are complicated and not (yet) well understood. Running a designed experiment and analyzing the results (both statistically and graphically) provides a quantitative basis for trade-off analysis.

Preliminary Results

We now present some preliminary results from an initial experiment. These are intended to be illustrative of the types of analytic products and insights that can result; more detailed explorations and analyses are needed before developing actionable recommendations. Table 2 lists the factors, their descriptions, and the low and high values over which we vary their levels. In all, we vary 13 factors for a total of 1,025 factor combinations, called design points (DPs). Our design is based on a nearly-orthogonal Latin hypercube with 65 design points (Cioppa & Lucas, 2007), so each factor can be explored at up to 65 different levels. For comparison purposes, a brute-force approach to studying 13 factors at 65 levels each would require over 3.6 septillion design points! Because our model is stochastic, we replicate each design point 20 times to reveal the variability in the system. It took roughly 8 hours to complete the 20,500 runs (simulated 180-day operations) on a single laptop.

Table 2: Factors and Factor Ranges for Initial Experiment

Factor	Description	Low level	High level
external resupply time	Wait time for logistics node resupply (days)	2	10
max wait time	Maximum time logistics vehicles wait before departing (days)	0.5	3.0
number of LV	Number of vehicles per logistics node	8	20
log node min	Triangular distribution minimum value	0.5	1.5
log node max	Triangular distribution maximum value	2.5	3.5
log node mode	Triangular distribution mode	1.5	2.5
onload mean	Mean time (days) to load vehicle (gamma distribution)	0.25	0.65
onload shape	Shape parameter for loading vehicle (gamma distribution)	8	12
offload mean	Mean time (days) to unload vehicle (gamma distribution)	0.1	0.5
offload shape	Shape parameter for unloading vehicle (gamma distribution)	8	12
enemy attack	Probability of an enemy attack	0.01	0.1
enemy kill	Probability of an attack resulting in destruction of the logistics vehicle	0.01	0.03
maintenance	Probability of an unscheduled maintenance issue	0.5	0.25

There are many potential measures of performance (MOPs) or measures of effectiveness (MOEs) that can be examined. For illustrative purposes, we focus on a single one: the average number of requests in queue awaiting processing. This time-weighted average is calculated for every simulation run. We then average the results over the 20 replications for each design point to obtain 1,025 values of MOE = Mean(avg requests in queue).

Figures 3 and 4 show the results of applying stepwise regression to fit a response surface metamodel for this MOE. The stepwise algorithm used considered main effects, quadratic terms, and two-way interactions for inclusion in the final model. Figure 3 indicates that the regression model fits reasonably and explains 90% of the variability in the data. Figure 4 contains a numeric and visual display of the model's terms, all statistically significant ($p < 0.0001$). The horizontal bars indicate the direction and magnitude of each term. The "tornado" visual results from having sorted the terms from greatest impact to least impact. We see that the top two influential factors are the number of LVs and external resupply time—both of which are decision factors over which the Marine Corps can exercise control.

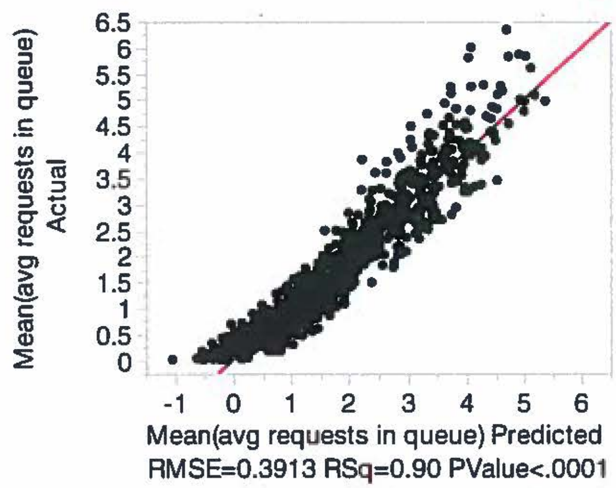
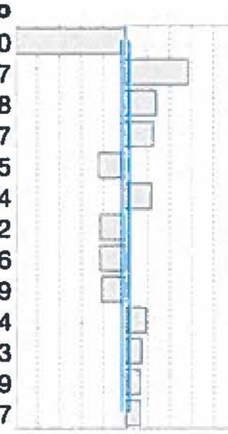


Figure 3: Regression Summary Results

Term	Estimate	Std Error	t Ratio
number of LV	-0.245	0.0034	-71.30
external resupply time	0.209	0.0051	40.97
enemy attack	9.4267	0.4581	20.58
onload mean	1.8833	0.1037	18.17
log node min	-0.709	0.0409	-17.35
enemy kill	28.717	1.7055	16.84
(external resupply time-6.06244)*(number of LV-14.0312)	-0.023	0.0015	-16.02
log node mode	-0.652	0.0409	-15.96
log node max	-0.63	0.0409	-15.39
(number of LV-14.0312)*(number of LV-14.0312)	0.0142	0.0011	13.04
offload mean	0.9917	0.0979	10.13
(enemy attack-0.055)*(enemy kill-0.02016)	636.52	65.015	9.79
max wait time	0.1568	0.0166	9.47



Note. p-value < 0.0001.

Figure 4: Important Regression Terms, All Statistically Significant

As it is sometimes difficult to understand the interactions and quadratic effects from just the regression coefficients, we find that an interaction plot can be a useful graph. Figure 5 contains the set of plots for the regression's two-way interaction terms. The presence of non-parallel lines is a visual indicator that two factors interact with each other, meaning that the effect of each factor on the response depends on the value of the other factor. We now give an interpretation of the interaction that occurs between external resupply time and number of LV. There are two complementary visual representations of this interaction. We will describe the interaction plot that appears in the fourth row, third column. When the number of LVs is at its highest value in the experiment (=20 and represented by the blue line), then decreasing external supply time over its range decreased average requests from (approximately) 0.7 to 0.5. This is not a huge difference because requests awaiting fulfillment were kept fairly low regardless of supply time due to the luxury of the larger number of vehicles. However, when the number of LV was at its lowest value (=8 and represented by the red line), then decreasing supply time had a much larger effect—in this case, average requests decreased from close to 5 to under 2. In other words, supply time has a greater impact when there are fewer LVs; in fact, decreasing the supply time can help mitigate the problems associated with having fewer vehicles.

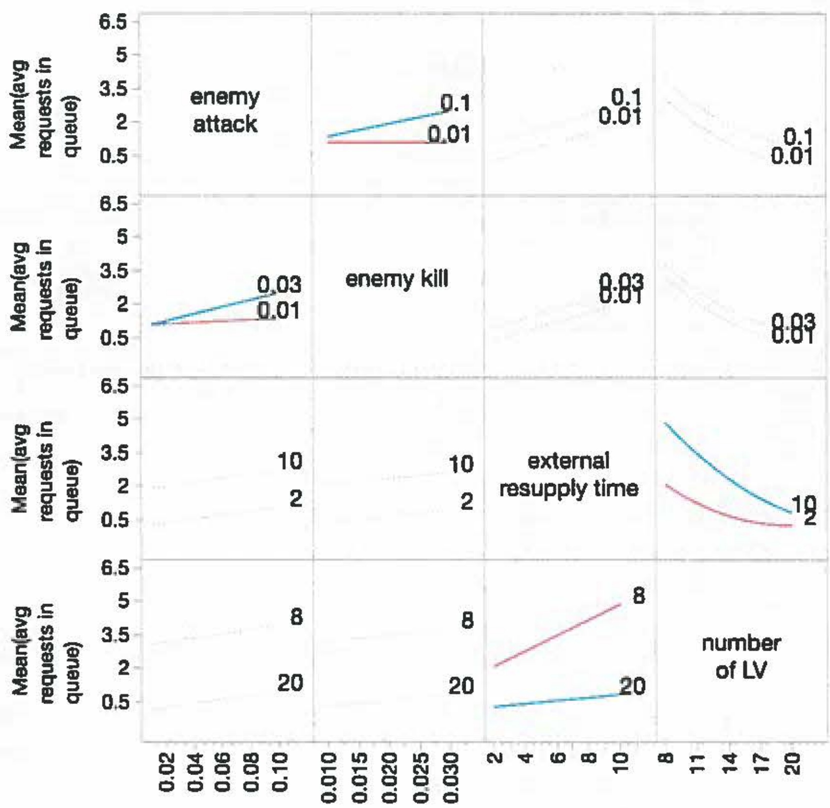


Figure 5: Interaction Profiles

Finally, regression is not the only type of metamodel possible. An alternative is the partition tree, as shown in Figure 6. The recursive partitioning technique that is used to produce the tree identifies factors and cut points that best predict the response. Recursive partitioning nicely complements the use of regression modeling because (1) it is a nonparametric approach (so it does not require any assumptions of the underlying data); (2) it reveals insight about interesting thresholds or cut-points that may be associated with jumps or discontinuities in the response; and (3) the “decision tree” structure that results is generally easily communicated and intuitively understood, even by those without a technical background.

We first notice that the two factors that appear in the tree are the same top two influential factors from the regression. The first (top-level) split in the tree occurs on the number of LVs, so this is a highly influential factor. The left and right nodes of this split indicate that when the number of LVs is greater than or equal to 13, the average number of requests is 1.08, but when the number of LVs is less than 13, then the average number of requests increases to 2.71. As a subsequent split reveals, when we are able to increase the number of LVs to 16 or more, the average number of requests drops to 0.82. The other factor that appears in the tree is external resupply time. In the cases where 16 or more LVs are available, dropping resupply time to under five days is able to reduce the average number of requests to 0.39 (close to zero). However, cases associated with fewer than 13 LVs and resupply time in excess of six days led to 3.3 requests awaiting fulfillment, on average.

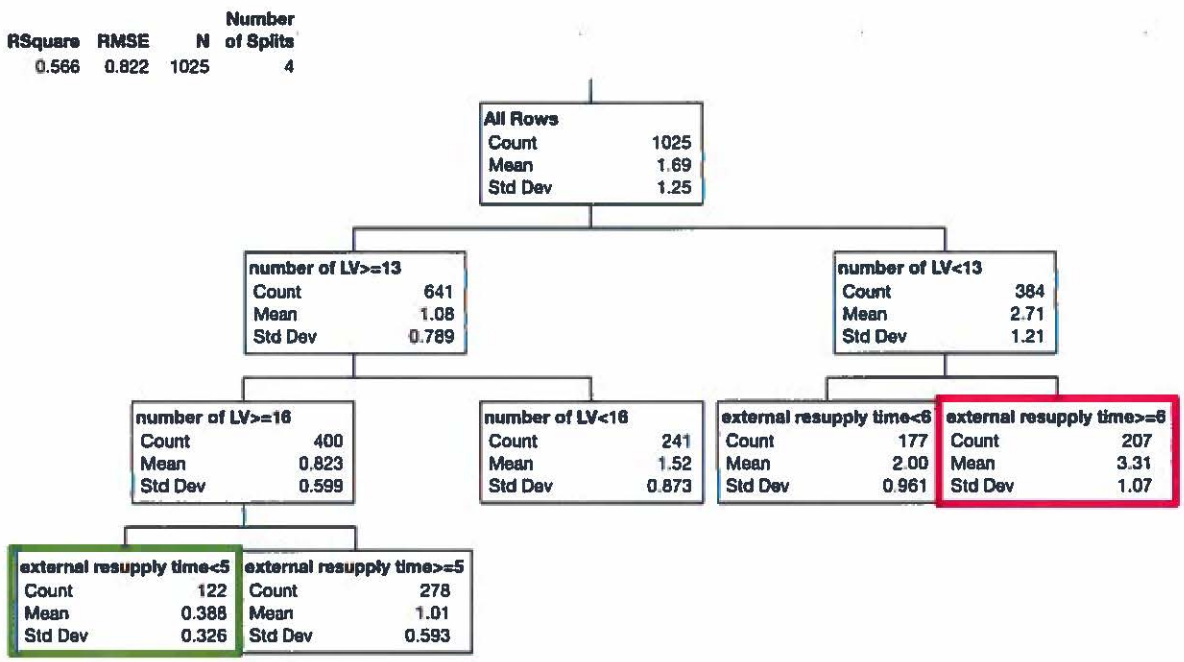


Figure 6: Partition Tree for Mean(Avg Requests in Queue) After Four Splits

With metamodeling approaches such as regression and partition trees, we can gain insight into which factors and interactions are most important, interesting cut points or “knees in the curve,” and which factors have little effect. Some of these findings may be contrary to initial intuition. However, there are other insights that can be gained as well from experimentation. As one example, we could identify which DPs (alternatives) met user-defined constraints on the response. Additionally, though we considered mean performance for these initial insights, we could go further and apply a loss function that captures both mean performance (does it meet a defined threshold?) as well as variability over random replications or uncontrollable/noise factors (more variability translates to higher risk). We may also consider multiple objectives, identifying if a trade-off is involved. We may reduce our set of alternatives that we need to consider by removing those that are dominated by others, leaving only those on the interesting Pareto optimal frontier. Finally, visual analysis through plots and graphs should always accompany and precede metamodel fitting, though for brevity we do not include it here.

We finally mention that all of this rich analysis is enabled through the application of efficient and flexible designs of experiment. Efficient designs enable experimentation over a number of factors and levels that is simply not possible through brute force (i.e., exhaustively sampling every possible combination). Efficient designs allow us to break the curse of dimensionality.

For more information and examples of data farming, and links to software and spreadsheets for constructing designs, see Lucas et al. (2015), Sanchez and Sanchez (2017), Sanchez et al. (2012, 2018), or the NPS SEED Center for Data Farming website at https://harvest.nps.edu.

Ongoing Work

In the second phase of this research, we plan to refine our simulation model and conduct further experiments, which could include a more detailed treatment and examination of how the quality, reliability, and time required to produce AM parts influence networked expeditionary logistics. Expertise about various properties and characteristics of different materials used in AM (e.g., polymeric materials, composite materials, and metal or alloy composition powders), as well as post-treatments required for the parts to achieve their final structural and physical characteristics, may guide the simulation model factors related to quality, reliability, and lead-times required for manufactured parts. Additionally, with an increased focus on the refinement of the manned-unmanned teaming concept (Department of the Navy, 2016, p.16), we plan to introduce the use of one or more unmanned vehicles into the model. Our second phase of research may then be guided by the following questions:

- How does the use of unmanned vehicles and AM affect the readiness of an expeditionary unit? What are the primary readiness drivers? Under what conditions do these either increase or decrease overall readiness?
- If parts made using AM differ in their characteristics from those made using current manufacturing processes, what are the ranges (or distributions) of the suitability of the parts for their intended use? Under what conditions are parts made using AM likely to be either more reliable, equally reliable, or less reliable than current parts?
- How does AM affect the life-cycle cost? What are the primary cost drivers? Under what conditions does AM either increase or decrease life-cycle cost?
- Are there win-win conditions where AM increases readiness while reducing costs? Are there lose-lose conditions where AM should be avoided because it reduces readiness while increasing costs? Are there conditions where trade-offs must be made between readiness and cost?

Summary

Our interest is in investigating the impact of AM on military logistics and life-cycle costs for Marine Corps expeditionary operations. We view AM as a potential transformative capability, but to realize its full potential for expeditionary operations, the Marine Corps logistics concept of operations must change.

Our work provides a template for augmenting the acquisition decision process by using simulation analytics—specifically, a data farming approach. Many characteristics of an

AM-capable expeditionary operational unit can be explicitly studied as factors within large-scale simulation experiments. Consequently, we can identify which sources of data (e.g., demand patterns, reliability, quality, printing and processing time, lead-time) or their interrelationships are the key drivers of readiness and performance. This might help program managers set initial requirements, determine what should be monitored most closely as AM programs are rolled out, or assist in estimating the potential benefits as new AM compounds or processes become available over time.

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